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Peer-to-Peer Energy Exchange in Solar Photovoltaic Systems and Battery Energy Storage Systems By TLBO Algorithm

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ABSTRACT

This paper presents a Peer-to-Peer (P2P) energy trading model in micro-grids that considers distributed solar photovoltaic systems (SPVs) and battery energy storage systems (BESS) by the TLBO Algorithm. It aims to minimize customer costs and increase profit by optimizing charging, purchasing, and selling decisions. For this purpose, two scenarios are studied. In the first scenario, the primary energy system includes SPVs, loads, and BESS to optimize the charge/discharge of the energy storage systems. In the second scenario, it is assumed that in addition to the SPVs, loads, and BESS, a neighbouring fossil fuel-fired micro-grid is connected to the primary energy systems, allowing peer-to-peer (P2P) energy trading with it. According to the results, trading in the second scenarios on a winter day lead to 14.53 $ per day, compared to the first scenario with 11.53 $. In addition, the neighbouring fossil fuel-fired micro-grid in the second scenario, which has created the possibility of energy exchange between micro-grids, has led to an increase of about 21% in the profit of the primary power grid. Based on the results, this approach seemed to be helpful for micro-grid operators to make the most economical decisions.

1. Introduction

Renewable-based energy sources, like solar photovoltaic systems, fuel cells (FCs), and geothermal power plants, constitute the majority of the emerging power grid industry segment [1-3]. This represents a shift from centralized power plants to more localized, distributed power generation, particularly in urban, industrial, and community areas [4-8]. Therefore, it is essential to integrate two or more sources to provide continuous power and minimize the cost to the customer via an intelligent energy management system (EMS) [8-10]. Nowadays, economic perspectives are an essential issue in the evolution of the energy grid. They have always been the main priority in planning energy systems. Due to energy source technology and pattern evolution, energy markets are decentralized and moving forward to a digital market. Peer-to-peer (P2P) energy trading is entering the energy sector for distributed generation (DG) [11]. P2P application lets individual consumers become consumers and makes it possible to share their excess energy with neighbors [12-15]. On the other hand, instead of grid operators, the microgrid operators are maintaining energy balance in each vicinity and managing electric consumption. They supervise the capacity of the controllable line for the exchange of energy [16, 17]. In P2P energy exchange, additional intermediaries' costs can be considered easily by distribution costs in addition to the microgrid electricity prices [11].

The results of a P2P energy trading platform simulation have been presented that this platform can

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help network and congestion management and lead to more DG sharing within a community [18, 19]. The win-win situation can achieved by looking for a reasonable exchange price and making a deal in the moment. Energy market players are not limited to conventional power plants and loads in the P2P energy trading ecosystem and each customer could trade electricity at a marginal price by the time of use (TOU) price and higher than feed-in tariffs (FIT). This provides motivating profit for sellers and savings for buyers [20]. Recent studies found that a 30% lower energy cost for households is reachable in the P2P energy trading model compared to traditional energy exchange methods[13]. The reference [21] presents a multi-objective model that uses a future-day stochastic scheduling model to lower costs for ten renewable-based microgrids, which include solar photovoltaic and wind turbines (WT) with demand response and energy storage. In the Reference [22], all microgrids are equipped with 100% renewable energy sources, including solar photovoltaic systems (SPVs) and wind turbines (WTs), thereby reducing pollution. In addition to reducing interruptions caused by renewable energy, energy storage is an integral part of a dynamic energy balance. Microgrids have been modeled using autoregressive integrated moving averages and fast-forward selection methods to generate and minimize scenarios based on fluctuations in day-ahead market prices. Energy transmission has also been considered stable and reliable as a technique for managing and coordinating energy sharing between microgrids and energy grids in local environments. The effectiveness of the proposed model is verified using a case study of 24 modified IEEE buses. Interactive energy presents optimal scheduling for profit maximization among Home Microgrids (H-MGs) described in [23] presents an intelligent energy framework in which home microgrids (H-MGs) can cooperate in a multi-H-MG system by forming coalitions to gain market competition. In addition, considering demand fluctuations, renewable energy generation in multiple H-MG can be achieved with demand-side management strategies that try to use mechanisms to produce a smoother demand curve. Based on a recent study, interactions between multi-carrier energy systems provide the opportunity to achieve affordable and clean energy by using energy resources more efficiently. For example, [24], a transactional energy (TE) framework is proposed for optimal energy management of multiple energy hubs. Each hub is a multi-carrier energy system that performs daily energy management to plan its electrical, heating, and cooling demand profiles and manages its internal energy resources to reduce total energy costs and CO2 emission levels. By reviewing the state-of-the-art literature, it can be said that the optimal and economic planning of the energy system based on bilateral energy exchange, focusing on the planning of BESS and considering SPVs, has not been studied well. This paper examines the exchange of electricity between microgrids connected to and against the grid. It takes electricity tariff changes during the day into account, which optimizes resource scheduling.

With the rapid growth of optimization problems, efficient optimization methods are presented. Early works focused on mathematical techniques which faces difficulties in the newly-emerged big-sized problems. This leads researchers to develop different meta-heuristic algorithms, such as swarm intelligence algorithms (SIAs), evolutionary algorithms (EAs), and algorithms based on biological phenomena[18-25].

However, some specific control parameters are defined in algorithms that must be set by the user in such algorithms These specific parameters of the algorithm require reasonable and appropriate tuning and are essential for these algorithms. Therefore, in various scientific research, efforts should be made to overcome this issue. One of these methods is the optimization algorithm based on training and learning (TLBO), which can be used without any adjustment parameters.

In Section 2, after the definition of topology, the proposed method has been described in detail. Section 3 describes the optimization method, and Section 4 illustrates the analysis and discussion of the results. The paper concludes with Section 5.

2. Proposed Method

2.1. Energy trading model for microgrids based on peer-to-peer exchanges

As shown in Fig. 1, a microgrid with renewable energy sources can exchange energy with the main grid and other microgrids. This energy exchange between microgrids is limited by technical and economic issues. The presence of BESS can improve the conditions for energy exchange between different areas[10-12]. Consequently, microgrid operators can increase their profitability. This structure is illustrated in Fig. 2, where the local electric load is placed near a renewable energy source and BESS in the left micro-grid and the right side micro-grid can be indirectly supplied by the main grid, BESS, or adjacent energy systems.

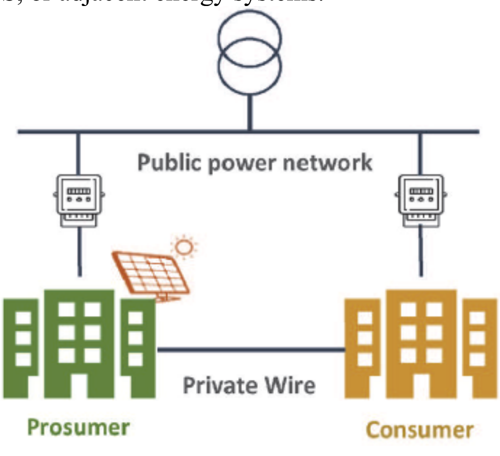

Fig. 1. Example of energy exchange in connected microgrids without direct main grid intervention [12].

Energy exchange between these parts depends on the energy tariff. Based on this micro-network tariff, it can decide to sell, buy, or store energy in different situations. In such a structure, maximizing profit is the main goal of the energy management system for this micro-grid by providing the required energy from the available resources at the lowest cost. Due to the presence of storage, the operation planning should be done beyond 24 hours in order to effectively utilize all installed equipment.

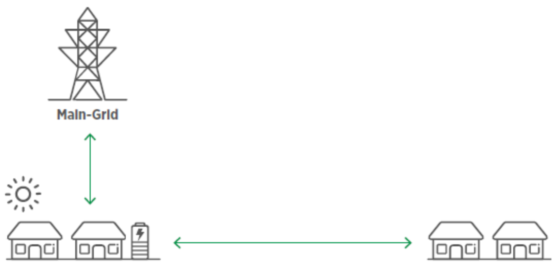

Fig. 2. Energy storage presence in a microgrid[12]

2.2. Constraints and problem definition

In this paper, the first microgrid includes solar cells, energy storage, and co-generation of electricity and heat (CHP) units. Each part has been modeled based on [25]. The operational constraints and limitations must be considered in accordance with economic factors in the optimization problem to achieve the optimal operational strategy. Therefore, the fitness function should include costs and revenues.

The constraints and limitations that must be considered in the optimization problem in order to achieve the optimal efficiency of energy systems are in the form of relations (1) - (5)

$$E_{e,min} < E_e(t) < E_{e,max} \qquad \forall t \tag{1}$$

$$E(t+1) = E(t) + P_c(t).\Delta t.\eta_c^e - P_d(t).\Delta t.1/\eta_d^e \tag{2}$$

$$0 < P_c(t) < P_{c,max} \tag{3}$$

$$0 < P_d(t) < P_{d,max} \tag{4}$$

$$P_c(t).P_d(t) = 0 \qquad \forall t \tag{5}$$

The hourly state of charge (SOC) is defined by $E_e(t)$. The SOC value should be limited according to (1) and updated according to (2) in each time interval. In (2), the values of η_c^e and η_d^e express the charging and discharging efficiency of the battery respectively, and limited between 0 and 1. This stipulation means that part of the power can be stored or restored from the battery storage system. The efficiency of charging and discharging also shows the amount of energy wasted during charging and discharging cycle. In addition, the storage capacity of the battery has a maximum and a minimum, which is mentioned in (1).

The charging and discharging power of the battery is expressed by $P_c(t)$ and $P_d(t)$ respectively, while their upper and lower limits should be maintained between pre-defined values by (3) and (4) [25].The maximum charging and discharging power of the battery is expressed by $P_{c,max}$ and $P_{d,max}$ respectively. It is assumed that the battery can only be charged or discharged in each time interval. This rule expressed by (5). The initial amount of energy in the battery E(t =0) is equal to E0, and final value of E(t) should be equal with initial value of E0.

The following relations define another constraints in controlling the amount of charging and discharging, which should be taken into account during implementation.

$$P_c(t) - P_c(t-1) \le P_{d,max} \tag{6}$$

$$P_c(t) - P_c(t-1) \ge P_{c,max} \tag{7}$$

These relationships are expressed in equations (6) for the charging cycle and (7) for discharge, indicate the amount of power input and output to the battery during one hour follows a threshold limit.

Variable efficiency and fixed efficiency of energy conversion of CHP, are defined by the following equations.

$$P_{E,i}^{chp} = \begin{cases} a_i^{chp}\phi_i^{chp} + b_i^{chp}T_{s,i}^{chp} + c_i^{chp} \\ \quad r_{1,i}\phi_i^{chp,\max} \le \phi_i^{chp} \le \phi_i^{chp,\min} \\ a_i^{chp}\phi_i^{chp} + b_i^{chp}T_{s,i}^{chp} + c_i^{chp} - w_{1,i} \\ \quad r_{2,i}\phi_i^{chp,\max} \le \phi_i^{chp} \le r_{1,i}\phi_i^{chp,\min} \\ a_i^{chp}\phi_i^{chp} + b_i^{chp}T_{s,i}^{chp} + c_i^{chp} - w_{1,i} - w_{2,i} \\ \quad \phi_i^{chp,\max} \le \phi_i^{chp} \le r_{2,i}\phi_i^{chp,\min} \end{cases} \tag{8}$$

$$w_{1,i} = (r_{1,i}\phi_i^{chp,\max} - \phi_i^{chp})\mu_{1,i} \tag{9}$$

$$w_{2,i} = (r_{2,i}\phi_i^{chp,\max} - \phi_i^{chp})\mu_{2,i} \tag{10}$$

$$f_i^{chp} = (3412/40611) \times \left(\frac{P_{E,i}^{chp} + \phi_i^{chp}}{\eta_i^{chp}}\right) \tag{11}$$

The (8) shows the variable efficiency performance of a CHP. In (9) and (10), μ_1 and μ_2 are positive coefficients that determine how much the production power is affected by efficiency variability. In addition, r_1 and r_2 describe change in generated power. With known amount of thermal and electrical power produced by this equipment, it is possible to calculate the flow rate of the gas consumption based on equation (11) [26].

In equation (11), η_i^{chp} is the overall efficiency of CHP. To calculate the required gas in standard cubic meters (SCM), the output of equation (11) multiplied by the appropriate conversion factor.

Another renewable source in this study is solar panel whose production rely on the amount of absorbed sunshine in the area. The output power of photovoltaic modules define by following equations [27].

$$P_{pv} = P_{STC}\frac{I_s}{1000}[1 + \gamma(T_c - 25)] \tag{12}$$

In (12), P_{STC} is the maximum power of the photovoltaic module under standard test conditions. The I_S is the solar radiation on the surface of the photovoltaic module. In addition, γ is the temperature coefficient of the photovoltaic module and T_c is the temperature of the photovoltaic cell (module) which is obtained from this equation:

$$T_c = T_a + \frac{I_s}{800}(T_{NOCT} - 20) \tag{13}$$

In (13) where T_a is the ambient temperature and T_{NOCT} is the nominal cell temperature.

2.3. Power balancing and Load Sharing

The sample microgrid shown in Fig. 3, includes sources as input and load as output. Genraraly, load of the micro-grid could be a combination of electric and thermal energy demand. There is also a battery that stores excess input energy and discharges it during peak hours. The input and output energy equations of the micro-grid can be expressed by (14)

$$P^G = P^{load} - P^{PV} \pm P^{battery} \tag{14}$$

In (14), P^G is the injected or delivered power from the main grid, P^{PV} is the power produced by the photovoltaic system, and finally, $P^{battery}$ is the battery power. Obviously, negative P^G means selling power to the grid, and otherwise, it means energy buying.

Since the optimization problem is solved for the microgrid, as a load distribution problem, it is possible to ensure that the equality condition in (14) is satisfied. Although conventional methods of load sharing such as forward and backward do not have any prohibition in solving this problem. However, due to the lack of line restrictions in micro-grids, the problem can be modeled and solved as a single node.

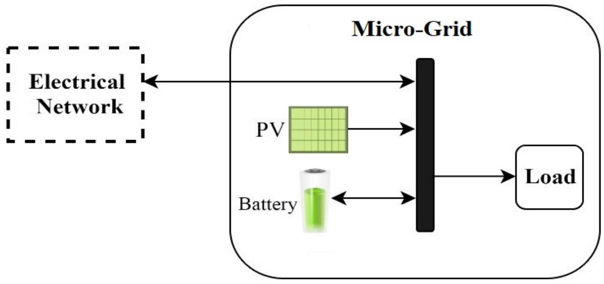

Fig. 3. Components of a micro-network equipped with different parts[12]

2.4. Energy exchange tariff

In the economic study of distribution networks and micro-grids, for achieving economic advantages and network loading reduction during peak times, different tariffs are proposed for different hours of the day and night. Three different tariffs can be considered as on-peak, mid-peak, and off-peak in studies of electric power trading [18].

In electric energy trading, when the network load is low, the price of energy will drop significantly. Increasing the electric load and getting closer to the peak time leads to an increase in the price. Microgrids tend to receive power from the grid during the low-load hours of the grid and sell their excess generated power to the grid during peak hours. This is more likely to happen in the presence of energy storage systems. Therefore, it should be noted that the planning effect of peer-to-peer energy exchange is considered with the presence of microgrids next to the upstream distribution network.

3. Optimization Method

The TLBO algorithm has two hase and will be explained in the next section.

3.1. Teaching-Learning Based Optimization (TLBO)

The TLBO algorithm is based on the philosophy of the teaching-learning process in the classroom. In this method, the teacher's impact on the learners' is simulated[28]. Like other swarm intelligence ones, this method is a crowd-based stochastic optimization algorithm. In contrast with many meta-heuristic algorithms, it does not require setting specific parameters. Due to some characteristics of the optimization algorithm based on training and learning, such as simplicity and no specific parameter settings, fast convergence, and easy implementation and at the same time efficiency, it has been widely used to solve many problems from different fields of science and technology. This algorithm has two phases, which are explained in detail.

Teacher phase

In this phase, students are trying to improve their knowledge and grades based on the level of information and knowledge of the teacher. This phase constitutes the first part of the algorithm, based on which a reference should be used to improve the fitness function. On the other hand, in this phase, the teacher tries to move the class average ($Mean^k$) to his knowledge level (Teacher) by his abilities. Therefore, this difference in the level of knowledge between the average class and the teacher can be shown in the form of (15).

$$Diference\_Mean^k = Teacher^k - TF^k \times Mean^k \tag{15}$$

In (15), TF^k expresses the learning coefficient. Based on this parameter, the average movement towards the teacher can be controlled. It is necessary to explain that the numerical value of this parameter is possibly chosen as 1 or 2. To do this, the expression round(1+rand(.)) is used, which can produce the numbers 1 or 2 because the round is used to render numbers.

$$X_{new1}^k = X_{old}^k + rand(.) \times Diference\_Mean^k \tag{16}$$

By the difference obtained from (15), each student expresses his position using the relation (16). Obviously, in the iterative process until reaching the final results, if the new state created has a better objective function (minimum or maximum) from the point of view of optimizing the problem, it replaces the previous solution. Otherwise, the same previous solution is maintained in the initial population until reaching a more optimal point. It should be emphasized that the results obtained from the teacher phase are considered as the input values of the student phase.

Learner phase

The second phase of the algorithm is known as the learner phase. In this phase, based on interactions and compromises between students themselves, the level of knowledge and information in the class is improved. In such a structure, in a random process, each student chooses another student and changes his knowledge level by (17).

$$X_{new2} = \begin{cases} X_i + rand(.) \times (X_i - X_j) & if \quad f(X_i) < f(X_j) \\ X_i + rand(.) \times (X_j - X_i) & else \end{cases} \tag{17}$$

$$i \neq j$$

If changing the level of knowledge related to the student in the training phase improves the fitness function, this position replaces the previous position in the primary population. Otherwise, the same previous position remains in the search space until a new result is obtained that is better than the previous one. As long as the algorithm is in the search space, similar to the teacher phase, the output obtained from the student phase is considered as the population input for the next iteration. In the last iteration, this result is declared as the global output. the pseudo-code of this algorithm is given in [27]

3.2. The objective function

Main goal here is profit maximizing related to the microgrid including renewable sources and energy storage. The microgrid is trading energy with the areas including the main grid and adjacent microgrid. The objective function defined as incomes and expenses from the sale and purchase of energy. Finally objective function is optimized by the proposed algorithm, taking into account the stated constraints to ensure that the required load of the microgrid is met. Therefore, the objective function (OF) defined as:

$$OF = max\left(\sum R_{U,i} - \left(\sum C_{U,i} + \sum C_{MG,i}\right)\right) \qquad (18)$$

In (18), $R_{U,i}$ is the income from energy selling to the grid, while $C_{U,i}$ is the total electric energy cost purchased from the grid and $C_{MG,i}$ is the total cost paid to the adjacent microgrid for It is an energy exchange. It is obvious that the direction of the power between the microgrids can be positive or negative. The price of electricity supplied by a diesel generator in the adjacent microgrid is determined by a quadratic function [22].

$$C_{MG,i} = C_{tie-line_{mg}} = aP_{tie-line}^2 + bP_{tie-line} + c \qquad (19)$$

Considering daily planning with an hourly resolution, in (19), T is the time interval (in hours). Also, $C_{tie\text{-}line\ mg}$ is the cost of purchasing power from the adjacent microgrid, and $P_{tie\text{-}line}$ is the power exchanged between the connected microgrids in hour i (in kilowatts).

The electric energy purchased from the grid can be defined by (20).

$$C_{U,i} = T \times MU_i \times C_{U_b} \times P_{U,i} \qquad (20)$$

Where MU_i represents the electricity tariff price at hour i, C_{Ub} is the maximum price of purchased electricity, and $P_{U,i}$ is the electricity injected from the adjacent microgrid.

4. Simulation Results

The main goal of this work is to obtain the optimal generation, stored and exchange of power in order to maximize the profit of the microgrid. Therefore the short-term planning of the system for the next day is done through a case study in a multi-zone system. Also, direct energy exchange between interconnected microgrids has been modeled to examine their integration in energy exchanges.

The case study includes the main grid and two microgrids. The first microgrid includes the electric consumer, solar resources, and the energy storage system. The second microgrid consist of diesel generator with simultaneous production of heat and power.

Two different scenarios are implemented to show the effectiveness of the proposed method by numerical studies. Power exchange tariffs are considered according to Table I [28].

Table I. Electricity tariffs for different time periods [29].

Time period	Buy coefficent	Sell coefficent
on-peak (17-22.9-12)	1	0.56
mid-peak (13-16)	0.89	0.45
off-peak (1-8 ‹23-24)	0.78	0.34

This table shows the electricity tariff in three periods. The maximum cost of electric energy is 0.13 $ per kilowatt-hour, which is intended for the purchase of electricity during peak periods.

The solar power system installed in the first microgrid needs information such as radiation and temperature in the region to produce power at its output. Irradiance and temperature data by hour for a sample solar system are obtained from [29].

The hourly changes of the power consumption (electricity) of the first microgrid are based on the information from [30].

It is also assumed that the SOC of battery storage is equal to 5 kWh at the initial time. Other main parameters of the battery, such as charge and discharge rate, efficiency, and maximum and minimum capacity of the battery, are stated in Table II.

Table II. Initial condition.

Time period	Value
Length of time interval, T, (hours)	1
Primary energy in the battery (kWh)	5
Battery charging efficiency	0.9
Battery drain efficiency	0.9
Battery Capacity, (kWh)	25
Minimum energy in the battery (kWh)	2.5

To verify the effect of peer-to-peer energy exchange, two scenarios are defined to check the proposed optimization method.

4.1. First scenario: microgrid just connected to the network

In this scenario, the second microgrid and its equipment are not discussed, the interaction between the distribution network and the first microgrid with equipment such as a battery energy storage system, solar system, and load is considered. Firstly, the generated power of the solar system (as the only source in this microgrid) is examined. The amount of output power of the solar strongly depends on the radiation and is not very sensitive to the ambient temperature [27].

During different times when the cost of supplied electricity in the main grid is high, the microgrid can supply its demand from solar sources or use batteries. Table III describes the amount of generated and exchanged energy with the main grid.

Table III Power transfers in the network on a winter day (first scenario)

hour	Buy from microgrid	Selling to the network	Battery power	hour	Buy from network	Selling to the network	Battery power
1	0	0	-1847.1	13	0	9571.24	0
2	0	0	-5097.0	14	0	5624.53	0
3	0	0	-4577.0	15	0	8574.44	0
4	0	0	-3067.0	16	0	4489.18	0
5	0	0	9123.4	17	0	7695.18	0
6	0	4210.5	0	18	0	0	-3508.1
7	0	4496.2	4640.5	19	7284.2	0	-7125.4
8	0	7315.11	5990.10	20	0	0	-1115.7
9	0	1741.39	0	21	4815.28	0	-3415.10
10	0	4589.43	0	22	7068.32	0	0
11	0	6394.28	0	23	3793.6	0	0
12	0	6344.38	0	24	7773.6	0	0

When the cost of purchased electricity from the grid is low, the microgrid can supply electricity from the grid and even store its excess in the battery to sell in other hours. This planning maximizes the profit of the microgrid owner.

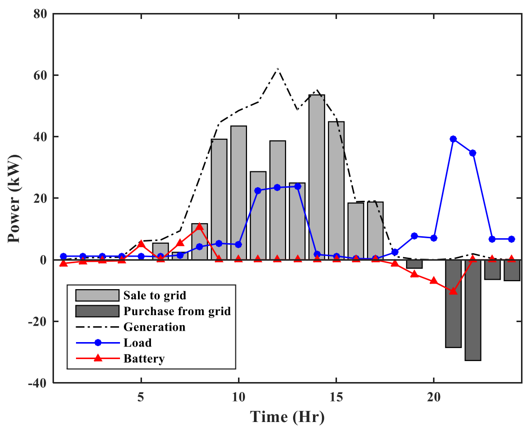

Fig. 4 The result of optimal planning in the first scenario.

In Table III the second and third columns show the power purchased and sold from/to the grid, respectively. The last column describes how BESS takes part in the system. Fig. 4 shows early hours production of renewable energy sources is less than energy consumption of the microgrid, so the battery is been activated to compensate the energy shortage.

Then, with the increase in solar energy production due to the sun's radiation, the microgrid's energy requirement is provided. The excess energy is managed by BESS. Due to the high price of buying electricity, energy is sold to the grid. Late at night, electricity production from renewable energy sources decreases again. Hence, the lack of microgrid energy consumption comes from BESS and the remaining energy demand, purchased from the grid.

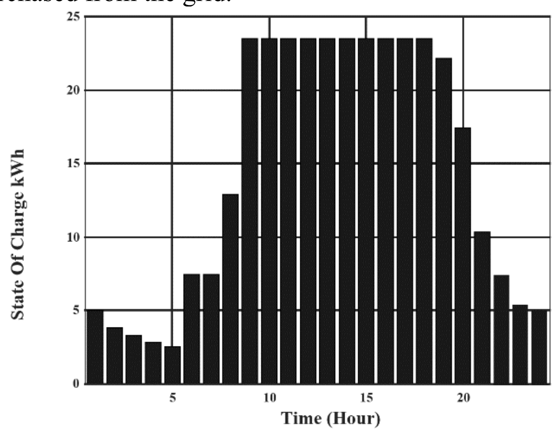

Fig. 5 Battery behaviour in the first scenario.

Fig. 5 shows that in the early hours, sufficient energy is stored in BESS, and then the battery SOC decreases due to energy needs. BESS stored energy equals 100% near 9:00 AM due to maximum renewable energy generation from sources. At the end of the day, again, storage is depleted due to BESS energy usage.

Finally, Table IV describes income from selling energy to the grid and the cost of buying energy from the grid for 24 time periods. The summation of the fourth column values is the maximum system profit per day.

Net zero summation of simultaneous buying and selling occurs during some time spans in a day. Because microgrid electric energy is directly supplied from the BESS at these times. Therefore, no electric energy is purchased from the main grid at these times.

There will also be no network sales. Based on Table IV, it seen that costs ultimately lead to the final optimal value, which is a kind of confirmation of the correctness of the results.

Table IV Power transfers in the network on a winter day (first scenario)

hour	Profit from sale	The cost of buying	difference	hour	Profit from sale	The cost of buying	difference
1	0	0	0	**13**	4600.1	0	4600.1
2	0	0	0	**14**	1334.3	0	1334.3
3	0	0	0	**15**	6242.2	0	6242.2
4	0	0	0	**16**	0793.1	0	0793.1
5	0	0	0	**17**	0980.1	0	0980.1
6	2396.0	0	2396.0	**18**	0	0	0
7	1083.0	0	1083.0	**19**	0	3547.0	-3547.0
8	5185.0	0	5185.0	**20**	0	0	0
9	8519.2	0	8519.2	**21**	0	7026.3	-7026.3
10	1638.3	0	1638.3	**22**	0	2519.4	-2519.4
11	0849.2	0	0849.2	**23**	0	6469.0	-6469.0
12	8126.2	0	8126.2	**24**	0	6872.0	-6872.0
	-	-	-	**Total**	**1744.21**	**6432.9**	**5312.11**

4.2. The second scenario: microgrid connected to a network and adjacent to other microgrids

In this scenario, it is assumed that a microgrid is connected to the primary energy system, allowing peer-to-peer (P2P) energy trading with it. The microgrid is powered by a gas-powered generator, renewable energy sources, BESSes, primary grids, or adjacent systems. The existing fossil fuel-fired microgrid, whose cost function is defined in (8), has coefficients of a=0.0024, b=0.0118, and c=0.2940. The temperature of this equipment is assumed to be 90 degrees Celsius.

It is obvious that the amount of gas purchased by the second microgrid depends on the consumption of the CHP diesel generator.

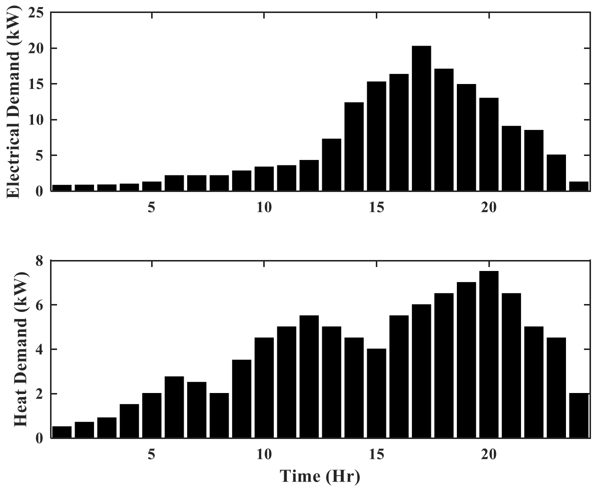

Fig. 5 The amount of electrical and thermal load in the second microgrid

The hourly amount of electrical and thermal load of the second microgrid that must be supplied in kW is shown in Fig. 5.

The price of natural gas in gas distribution networks is considered a rate of 0.14 units per cubic meter fixed. The income of the second micro-grid is obtained from the difference in the amount of energy sales compared to the natural gas cost. The amount of exchanged power between two microgrids is illustrated in Fig. 6.

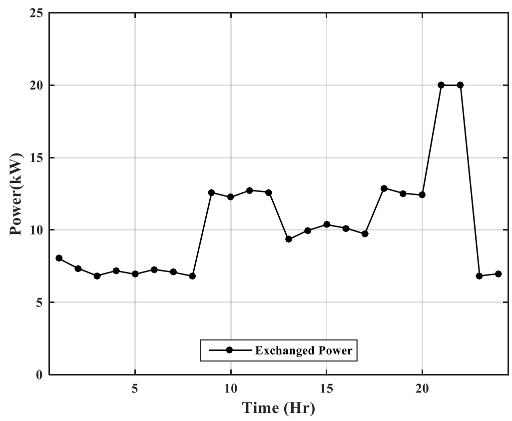

Fig. 6 Energy exchange between microgrids in the second scenario

In this scenario, the transfer limit between microgrids is considered to be 20 kilowatts by interconnection line. In this case, it should be determined which source provides energy to the other microgrid throughout the day.

That is obvious, the surplus generated energy at this time was sold to the power network or stored in the BESS. Like the first scenario, the algorithm maximizes the wholesome system profit. Optimization outputs are shown in Fig. 7.

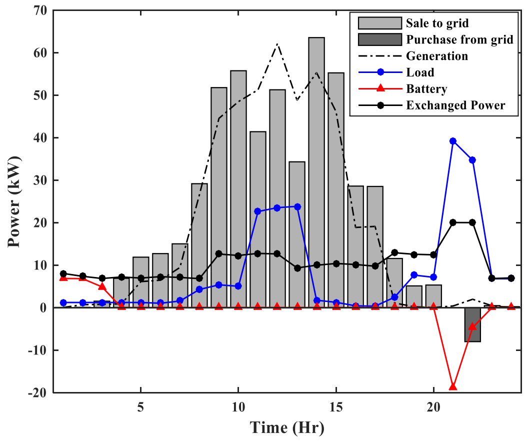

Fig. 7 The result of optimal planning in the second scenario

The convergence curve of the objective function in the second scenario is shown in Fig. 8 and it has been seen that the most optimal value of the target function, is about $ 14.05 per day.

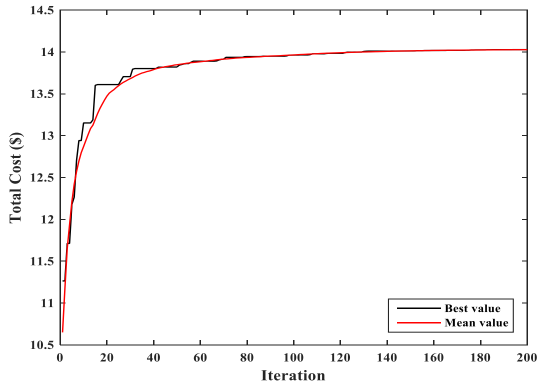

Fig. 8 The convergence curve of the objective function in the second scenario

Table V Hourly Power transfers between micro-grids in a day in Kwh (second scenario)

hour	CHP	Gas powered Generator	Exchanged Energy	hour	CHP	Gas powered Generator	Exchanged Energy
1	2400.0	3918.8	8589.7	**13**	4000.2	0159.15	1843.10
2	3360.0	6311.7	1686.7	**14**	1600.2	8842.19	7184.9
3	4320.0	5310.7	1305.7	**15**	9200.1	2441.23	9284.9
4	7200.0	1136.7	8913.6	**16**	6400.2	1150.23	4652.9
5	9600.0	7814.7	5057.7	**17**	8800.2	2684.27	9305.9
6	3200.1	0134.8	2089.7	**18**	1200.3	3797.26	4762.12
7	2000.1	8185.7	8939.6	**19**	3600.3	6110.24	0914.13
8	9600.0	6569.8	4923.7	**20**	6000.3	5009.22	1478.13
9	6800.1	0384.14	9342.12	**21**	1200.3	8776.25	9744.19
10	1600.2	7087.13	5421.12	**22**	4000.2	0526.26	9958.19
11	4000.2	9493.13	8247.12	**23**	1600.2	5932.9	7408.6
12	8126.2	0	8126.2	**24**	0	6872.0	-6872.0

The results of generated and exchanged energy in the second micro-grid, are given in Table V. Results of this table show that the participation of the CHP in providing electric power is weaker than the diesel generator. This is due to the fact that the amount of electric production for this equipment depends on its heat. In addition, this equipment is cost-effective with certain gas consumption, and it can provide the thermal load and participate in electric power generation, which is one of the advantages of such equipment.

5. Conclusion

This paper has studied microgrids that provide peer-to-peer (P2P) energy trading with the neighboring and upstream grid, as well as a battery for storing excess energy to minimize costs and increase profits. To clarify the distinction between the employed optimization method, two scenarios are studied.

In the first scenario, a power network grid with DG, load, and battery is assumed, and the advantages of DG storage are considered. In the second scenario, a microgrid containing fossil fuel sources for the peer-to-peer (P2P) energy trading market was placed near the primary power grid. TLBO algorithm employed for optimal operation of these microgrids, considering hourly electricity tariffs during one day. Due to the difference in the price of buying and selling electricity, the energy exchanges with the grid occur at optimal electricity prices. Based on the results, the profit from trading in the first scenario on a winter day was $11.53 per day. In the second scenario, the presence of the neighboring microgrid, with the possibility of peer-to-peer energy exchange between microgrids, has led to an increase of about 21% compared to the first, which was a significant increase. Based on the results, this approach motivates microgrid operators to make the most economical decisions.

6. References

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